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***Abstract*— This abstract describes a novel approach for handling brain-computer interfaces (BCI), that could be used for robotic applications. State-of-the-art approaches rely on the classification of covariance matrices in the manifold of symmetric positive-definite matrices. Functional connectivity estimators have demonstrated their reliability and are good candidates to improve the classification accuracy of covariance-based methods. This abstract explores possible application of functional connectivity in Riemannian BCI.**

I. INTRODUCTION

Brain-Computer Interfaces (BCI) consists of a device that translates brain activity into commands for control and communication[1]. BCI devices can be a valuable tool in the treatment of neurological disorders [2]. They can also constitutes a motor substitution in the case of neuroprosthesis by building alternative pathways [3]. Recently, an exoskeleton controlled by an epidural wireless BCI enabled a tetraplegic patient to walk [4]. This result constitutes a first proof-of-concept performed in the laboratory. Despite its clinical applications, many issues remain. The most limiting one is the inter/intra-subject variability or also known as "BCI inefficiency" [5]. Indeed, a non-negligible part of the users (between 15 and 30% [6]) cannot control the BCI device despite several training sessions. It clearly limits the BCI usability. Among the possible approaches to tackle this issue is the search of alternative features and classification tools that could enhance the discrimination of subjects' mental state. Relying on functional connectivity, our approach investigates the contribution of synchrony and/or phase to compensate potential misclassifications induced by power-related information available in golden standard methods.

II. RIEMANNIAN BCI

Approaches relying on covariance estimated over electroencephalographic signals are widespread in BCI. Covariance-based techniques are found in state-of-the-art spatial filters that are necessary for estimating subjects' mental command. These filters use Euclidean approach to process the symmetric positive-definite (SPD) covariance matrices. Riemannian BCI aims at working with covariance matrices directly on the manifold of SPD matrices, by adapting machine learning algorithms to such curved spaces. These Riemannian approaches outperformed filter-based methods on numerous datasets and have won several data competition[7], [8].

A simple, yet effective, classifier is the Minimum Distance to Mean (MDM). The barycenter of each class of training trial, in the sense of the Fisher distance, is used to determine the class of a newly seen trial. The trial is associated to the class with the closest barycenter. Applying a Fisher Geodesic Discriminant Analysis before computing the barycenter (Fg-MDM) yield robust results on experimental datasets [9].

III. PROPOSED METHOD

Functional connectivity (FC) enables to study the interaction between different brain areas [10], and has the potential to provide alternative features to BCI classifiers [11]. Here, as an exploratory study, we considered complementary undirected FC estimators associated to Riemannian geometry: spectral and phase estimators. In the following subsections, we defined the metrics computed between two given signals referred as $s_1(t)$ and $s_2(t)$ between two EEG sensors.

A. Spectral estimation

We computed one spectral estimator: the coherence (Coh), deduced from the normalized cross-spectral density S_{12} obtained from the two given signals $s_1(t)$ and $s_2(t)$, as follows:

$$Coh_{12}(f) = \frac{|S_{12}(f)|^2}{S_{11}(f).S_{22}(f)} \tag{1}$$

B. Phase estimation

As a phase estimator method, we worked with the Phase Locking Value (PLV), which assesses phase synchrony between two signals in a specific frequency band [12], as follows:

$$PLV = |e^{i\Delta\phi(t)}| \tag{2}$$

where $\Delta\phi(t) = arg(\frac{z_1(t).z_2^*(t)}{|z_1(t)|.|z_2(t)|})$
$\Delta\phi(t)$ represents the associated relative phase computed between signals and $z(t) = s(t) + i.h(s(t))$ the analytic signal obtained by applying the Hilbert transform on the signal $s(t)$.

It is possible to build SPD matrices from coherence and PLV estimators. Instead of using covariance matrices as input for Riemannian classifier, we propose to use functional connectivity matrices. These matrices contains information that is complementary to covariance and could help to achieve better accuracy or more robust decision.

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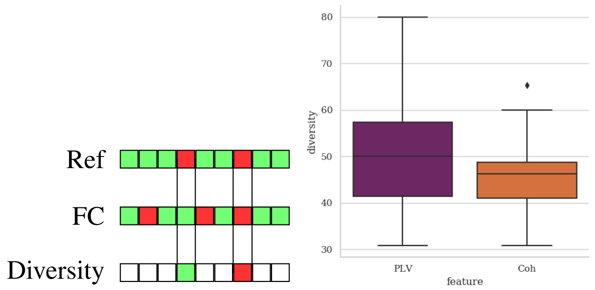

Fig. 1. Left: *Diversity* for a *FC* estimator is estimated over the samples that are not correctly estimated (red square) for the reference classifier *Ref*. Here diversity is equal to 50%. Right: Diversity of PLV and Coh + FgMDM classifiers estimated using cross validation on BCI Competition IV dataset. Reference is Cov + FgMDM.

TABLE I
CLASSIFICATION ACCURACY AVERAGED OVER THE NINE SUBJECTS

Approach	Mean ± Std
Cov + FgMDM	0.78 ± 0.13
Coh + FgMDM	0.47 ± 0.03
PLV + FgMDM	0.50 ± 0.03

IV. PROOF OF CONCEPT

We used the dataset 2a from BCI Competition IV that gathers electroencephalographic recordings from nine subjects (for a complete description of the dataset the reader can refer to [13]). In this work, we reduced our study to the classification of two classes (left vs right hand MI).

For a given FC estimator, we averaged the FC values within the 8-35 Hz frequency band. Computations were made using the Brainstorm toolbox [14].

We computed the performance obtained with the different tested approaches: Cov + FgMDM, PLV + FgMDM and Coh + FgMDM taken separately. First, we compared the accuracy (see Table I). Clearly, the approach consisting of considering each FC estimator separately did not give better results than the state-of-the-art (*i.e.* the covariance here). However, we further investigated our results to determine whether the Cov + FgMDM could benefit from the FC + FgMDM approach. For that purpose, we defined the diversity [15] as the proportion of trials misclassified by the Cov + FgMDM that have actually been correctly classified by FC + FgMDM. An illustrative example is proposed in Fig. 1. In the present work, we respectively obtained an averaged diversity of 50% with PLV and of 47% with Coh, meaning that on average, 50% of the misclassified trials by the Cov + FgMDM approach are correctly classified with the FC + FgMDM on Fig. 1. This finding suggests that Cov + FgMDM could benefit from an ensemble approach consisting of combining Cov + FgMDM and FC + FgMDM to compensate potential misclassification.

V. DISCUSSION & CONCLUSION

In the present study, we considered alternative SPD matrices as inputs of Riemannian BCI classifier, that are built on functional connectivity estimations. While using these matrices directly as features yield modest accuracy, or at least lower accuracy than covariance-based classifier, they could bring interesting opportunities when dealing with a larger number of classes.

A first direction is to adapt the classifier to the specific geometry of functional connectivity estimators. For example, some estimators like coherence are complex-valued and could benefit from a classifier designed to process HPD matrices. It is also possible to investigate the different estimators formulation to find those that lead to well-conditioned matrices.

Another direction is to combine the information coming from functional connectivity and covariance. It could be done with a machine learning perspective, relying on ensemble learning or feature selection, hence benefiting from the diversity of the features to build a robust and accurate model.

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